Comput Math Organ Theory (2010) 16: 29–60
DOI 10.1007/s10588-010-9064-4

Niche width and scale in organizational competition: A computational approach

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Published online: 4 June 2010

Abstract In some organizational applications, the principle of allocation (PoA) and scale advantage (SA) oppose each other. While PoA implies that organizations with wide niches get punished, SA holds that large organizations gain an advantage because of scale efficiencies. The opposition occurs because many large organizations also possess wide niches. However, analyzing these theoretical mechanisms implies a possible trade-off between niche width and size: if both PoA and SA are strong, then organizations must be either focused or large to survive, resulting in a dual market structure, as proposed by the theory of resource partitioning. This article develops a computational model used to study this trade-off, and investigates the properties of organizational populations with low/high SA and low/high PoA. The model generates three expected core "corner" solutions: (1) the dominance of large organizations in the strong SA setting; (2) the proliferation of narrow-niche organizations in the strong PoA setting; and (3) a bifurcated or dual market structure if both SA and PoA are present. The model also allows us to identify circumstances under which narrow-niche (specialists) or wide-niche (generalists) organizations thrive. We also use the model to examine the claim that concentrated resource distributions are more likely to generate partitioned or bifurcated populations. We also investigate the consequences of environments comprised of ordered versus unordered positions.

We appreciate the comments of many colleagues, but especially those of Jerker Denrell, Michael Hannan, Gael Le Mens and Jesper Sørensen. A preliminary version of the model and its findings was presented at the Nagymaros Group Workshop on Organizational Ecology, Istanbul, 2007; an updated version was presented at the Durham Business School conference on resource partitioning, Durham, UK, April 2010. Comments from participants at both events proved very helpful.

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Keywords Niche theory · Principle of allocation · Scale advantage · Size distribution · Simulation

1 Introduction

Organizational ecology's niche theory (Hannan and Freeman 1977) builds on the premise that a specialist (narrow-niche) organization designed well for a particular environmental state will outperform a generalist (broad-niche) organization in that same state. In order to perform adequately in other environmental states, the generalist organization must carry extra capacity, appearing as slack at any point. In other words, the specialist "maximizes its exploitation of the environment and accepts the risk of having that environment change" while the generalist "accepts a lower level of exploitation in return for greater security" (Hannan and Freeman 1977: 948). The theory thus imposes the constant-sum constraint holding that increased breadth of a niche comes at the expense of lowered appeal at some positions (Péli 1997; Hsu 2006). This assumption has come to be known as the principle of allocation (PoA).

Resource partitioning theory (Carroll 1985) presents an alternative theory of niche width based on different assumptions. This theory holds that generalists might actually benefit from participating in multiple activities if they can achieve larger scale. These scale advantages (SA) might be strong enough to outweigh any overhead costs of having a broad niche, thus giving the overall advantage to generalist organizations.

Hannan et al. (2007) propose a unified theory that attempts to resolve the tension between the two original theories. The unified theory uses several additional conceptual ideas, including audiences and engagement. It also provides explicit ways to model both the principle of allocation (PoA) and scale advantage (SA). In this article, we use the unified theory to develop a computational model to study these processes, making additional assumptions as needed to generate a simulation platform. Elements of the resulting model and findings transcend interest in organizational ecology. For instance, processes of scale advantage pertain to a broad class of economic and sociological phenomena, including scale economies in production and distribution, network externalities, attention allocation, and the efficacy of governmental lobbying.

In exploring the model, we address the key theoretical question: How does the tradeoff between niche width and scale work? The principle of allocation (PoA) says that the broader an organization's niche, the lower its appeal and effectiveness. Scale advantage (SA) suggests that breadth is sometimes also associated with beneficial effects because it may raise size capacity higher than with a narrow niche. Moreover, a broad niche often provides a guard against an uncertain future but the broader an organization's niche, the more likely it is to encounter competitors.

For most social scientists, the best answer to the above question would come from observing and comparing how organizational populations develop across time in contexts where PoA and SA processes operate at varying levels of intensity. Unfortunately, collecting detailed data on a single organizational population over its history proves to be a major undertaking, let alone multiple comparable populations. More importantly, for any real historical population, we can at best only infer indirectly the strength of unobservable processes of PoA and SA. And, the data one would use to make such inferences are likely to include outcomes of interest, meaning that the analysis could be conflated.

Because of the difficulty in testing the tradeoff empirically, we use here computational methods. Within a modeling framework, computational methods allow us to set precisely the strength of processes of PoA and SA (as well as other parameters) and to explore their implications for population developments including structure. In Harrison et al.'s (2007) view, computational methods prove especially valuable in examining the outcomes of multiple, interdependent processes such as those we investigate here.

To be more precise, we use the model to tell us how the distributions of niche width and size vary across populations with different levels of processes of PoA and SA. In other words, we assume specific PoA and SA functions and parameter settings as given characteristics of a population and its audience. Using Monte Carlo simulation techniques, we then generate, observe and compare populations with all kinds of combinations (including rare ones) of the processes including low PoA-low SA; low PoA-high SA; high PoA-low SA; high PoA-high SA and others. Such comparisons would be onerous (at best) with real-world observational data, but the simulation model yields analytical insight, much as laboratory experiments do when they isolate hard-to-discern processes. Moreover, because of the precision required to build the simulation, the model-building effort forces us to go beyond Hannan et al.'s (2007) specification and to render a more detailed version of the theory and related processes.

The theory we use contains several different components, each the subject of considerable attention. To keep our presentation from becoming overly complicated, we proceed in steps. First, rather than present the entire theory underlying the model, we describe each of the various components of the theory (audience, principle of allocation, scale advantage) and our associated modeling efforts—operationalizations—in turn, while providing some additional information about the credibility of each. Next, we demonstrate the general validity of the model by showing that it generates outcomes expected by theory and by previous empirical research.[1] Following that, we turn to questions about organizational action and environmental resource distributions. For organizational action, we aim to identify circumstances that favor narrow-niche organization (specialism), or wide-niche organization (generalism). For environments, we explore the speculation that concentrated resource distributions are more likely to generate partitioned or bifurcated populations.

2 The audience as niche

2.1 The niche

The first step in developing the computational model involves defining and conceptualizing the organizational niche. Organizational niches can be defined for a vast array

[1] In some contexts, analysts do not have much empirical or theoretical knowledge by which to assess the credibility of their model. Fortunately, in the case of niche width and scale, we have ample background research from organizational ecology and elsewhere to use in establishing validity.

of environmental properties, including the tastes of potential consumers and members, the availability of various kinds of input (e.g., human and financial capital), and legal and regulatory regimes. We follow most contemporary research and focus on consumers in markets for products and services.

In doing so, we build on and adapt the framework of Hannan et al. (2007) in envisioning four interrelated components of the niche: the audience, the resource space, engagement and actual appeal. We discuss the basic theoretical issues in turn, and describe our computational operationalization of each at the same time.

2.2 Audience and position

Hannan et al. (2007: 33) define an audience segment as "a differentiated set of all those agents with an intense interest in the organizations [in a domain], their activities and their products." Here we restrict the relevant audience to those in the domain-wide audience with an interest in consuming the products or other offerings of the set of producers being considered.

To link the model with prior research on organizational niches, we conceptualize the audience as distributed over a social or socio-demographic space (McPherson 2004). Tastes of the audience members are assumed to be a function of position in this space. For simplicity, we initially conceptualize the environment as composed of audience members located in unordered categories of social distinctions reflecting their tastes. We use the term social position to refer to an audience category in this space. We assume that the category has social standing and that it is recognized and used by audience members. Later in the analysis below, we incorporate distance into the social space; this complication allows us to investigate to what extent the ordering of resource positions or categories affects the outcome of resource partitioning processes.

We consider only prototypical tastes (for particular products or services) at each social position, which represent the modal tastes of the audience. For instance, Griffin (2006) reports survey results showing that in 1993 the music genre African-Americans most liked to listen to was "Gospel," while for Southern whites it was "Country" and for non-Southern whites it was "Rock." (Of course, some persons of each ethnic group do not subscribe to the typical taste but a plurality do.)

2.3 Resource space

In our model, the environment within which organizations operate is a resource space filled only with audience members with prototypical tastes. The audience members are demarcated by position along one dimension. But various positions in the space might have more or less strong prototypical tastes for the organization's products or services. And, the various positions might be populated by many or few audience members (potential consumers). Obviously, the potential maximum demand, or resources available to organizations at a position reflects a combination of both the taste at that position and the size of the audience there.

Rather than delve into the underlying factors separately, for simplicity we summarize the joint operation of taste and audience size at positions by an exogenously determined resource space. The resources available for organizations vary by position.

Locations with many market or environmental resources might reflect strong taste for the product, many audience members or both. For instance, day care services for humans tend to find many more audience members with relevant tastes among (families with) young children and the elderly.

2.3.1 *Operationalization of the resource space*

In our modeling setup, the environment or market of an organization consists solely of the audience. We model the environment by generating an exogenous two-dimensional space representing: (1) the social positions (x) of the audience (the positions are unordered), and (2) the potential maximum demand or resources $[R(x)]$ of the audience at each position, reflecting the strength of the prototypical taste and the size of the audience at x.

Imagine that the number of positions in an environment is fixed, at say 10. For the initial analysis, we use a simple setup for the positions: we regard positions as unordered categorical distinctions (this assumption is later relaxed). Because there is no meaningful ordering among the positions, we cannot measure the distance between any two positions; likewise, there are no neighboring positions and distant positions. For example, in the ethnic categories given above for taste in musical genre, African-Americans are no closer to Southern whites than to non-Southern whites.

Potential maximum demand represents the total amount of resource that can be obtained from a position by all organizations. In the simulation, the potential maximum demand in each position is set in the beginning and remains fixed throughout the simulation run. So, the environment might be envisioned as a histogram of demand across the 10 positions, or as a distribution of resources across the positions. Figure 1 provides a visualization of one possible resource distribution; any ordering of the positions a–j would be equivalent in our initial simulations.

2.4 Organizations

In this analysis, we model the evolution of a (fixed) constant set of organizations in the resource space. Over time, individual organizations can grow extremely large or shrink to infinitesimal size; they can remain narrow niche players throughout their

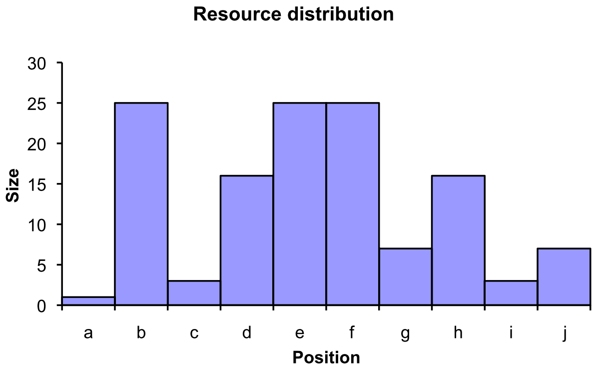


Fig. 1 Illustrative resource distribution

lives or expand to a breadth equal to the width of the resource space. We examine mean levels of organizational size and niche width as well as properties of the population distribution such as bifurcation, in both the steady state equilibrium and evolutionary trajectories.

Those readers familiar with research on resource partitioning may be surprised by the exclusion entry and exit processes from the simulations because they are the objects of much empirical work. However, we believe that the trade-off between PoA and SA should hold even if entry and exit processes are not present, and we believe that resource partitioning theory contains nothing to suggest otherwise. So, we contend that the joint operation of PoA and SA trade-off can produce bifurcation in organizational size and niche width distributions of on-going populations. We believe that if demonstrated, this novel implication on the theory would only strengthen the fundamental insights of resource partitioning.

There are also technical considerations. Since PoA and SA are organizational processes that operate in existing organizational populations rather than on entrepreneurs, we think that the additional assumptions required to incorporate entry processes would obfuscate understanding at this stage of model development (the model is already complex, as will be seen below). By contrast, organizational exit is implicitly modeled in the cases of organizations that shrink to a very small size. As Hannan et al. (2007: 220–223) demonstrate in Theorems 10.1–10.4, the essential insights of resource partitioning can be modeled even without entry processes.

2.5 Engagement

Within a market or environment, Hannan et al. (2007) argue that the conversion of prototypical taste into actual appeal depends on actions taken by an organization with respect to its product or service offerings—engagement of the market. They define engagement as the attention that producers pay to different subgroups in the audience. In their theory, a durable pattern of engagement converts prototypical tastes into actual appeal.

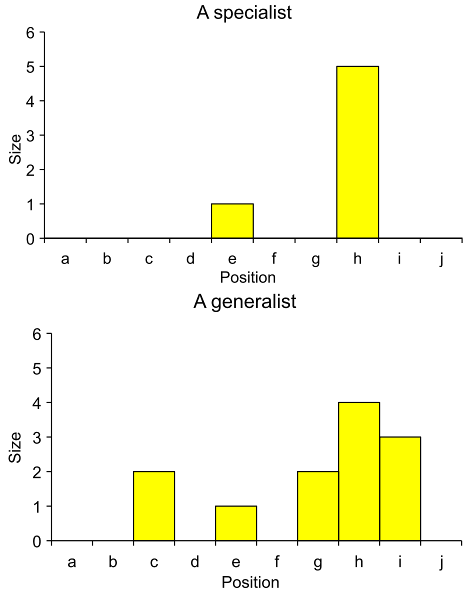
Engagement refers to a diverse set of activities undertaken by organizations and their agents, including: (1) learning about the idiosyncrasies of the local audience position and its aesthetics; (2) designing or redesigning features of the offering to make it attractive to that part of the audience; and (3) trying to establish a favorable identity in the relevant location(s). In many cases of interest, key engagement activities include developing and displaying credible signals of authenticity (Carroll and Swaminathan 2000; Baron 2004).

2.5.1 Operationalization of engagement

In the computational model, we assign each organization an engagement budget that reflects how much effort it expends in trying to win resources at positions in the environment. We let the engagement budget E of organization a at time t for position x be noted by $E(t, a, x)$.

In simulations reported below, we start each organization at only a single position, from which it can expand according to predetermined rules described below. In later

Fig. 2 Illustrative engagement budgets of a specialist and a generalist



steps, as described below, engagement budgets increase for larger organizations as a result of scale advantage. Initially, every organization starts out with a budget of the same size and it is allocated fully to the position the organization occupies.

Figure 2 gives an example of the engagement budgets of two organizations. In the first, engagement spans a relatively narrow part of the resource space, while in the second, engagement is spread more broadly.

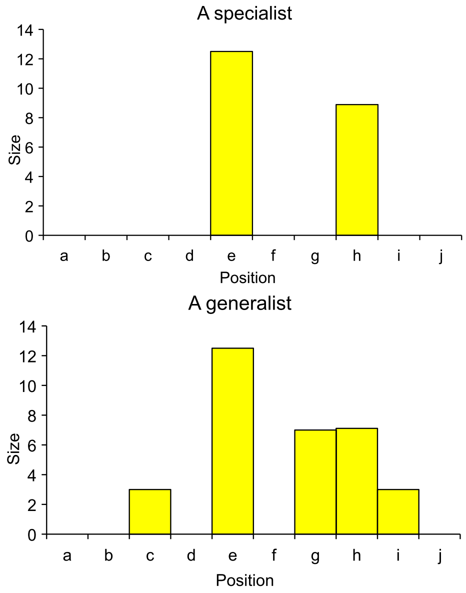
Note that in this operationalization, positioning as a generalist or a specialist represents an organizational choice, rather than the structure of the demand. While debatable, it seems to us (and many other organizational theorists) that many entrepreneurs and organizations adopt and attempt to succeed with market postures that in the end wind up being infeasible (Carroll 1993). In this sense, we believe that choices about niche width are more-or-less often "supply" driven. Of course, both views bear some validity but in our model demand mainly affects market viability.

2.6 Actual appeal

For modeling clarity, we assume that the intrinsic appeal of an offering is constant across all environmental positions and focus on its actual appeal.[2] With intrinsic appeal held constant, the actual appeal of an offering to the audience members at a social position depends both on the total resources available at a position and on the intensity of the organization's engagement at that social position (Hannan et al.

[2]This assumption enables us to understand more clearly how the model operates: allowing intrinsic appeal to also vary would add another level of exogenously imposed complexity. We hope to add this complication in later efforts, once we understand the simpler model. For now, we justify it in part by claiming that the setup we use does likely resemble contexts where firms face multiple (but similar) geographic markets.

Fig. 3 Illustrative values of actual appeal



2007). Without competition, organizations can expect to get more resources from engaged locations with abundant resources. Not engaging a position is essentially like not being present at the location; a firm can only obtain resources at those positions where it spends part of its engagement budget.

For example, although sports drinks such as Gatorade might have had latent attraction to athletic-minded individuals for much of the late twentieth century in the United States, it was not until Stokeley-Van Camp Inc. introduced and marketed (i.e., engaged the market with) Gatorade in 1969 that actual appeal became positive. Recruitment strategies by firms, universities, political parties, and other kinds of organizations also represent efforts to engage potential audiences in the market for members.

What happens if more than one organization engages at a given position? Such overlap in engagement reflects competition at the location. We determine the outcome of competition in a straight-forward way: organizations win competition at a given position proportional to their engagement relative to that of all other organization. That is, competitive outcomes are determined by proportional investments in engagement.

2.6.1 Operationalization of actual appeal

We operationalize the actual appeal of an organization's offering as the product of the resource level of a location and the organization's proportion of total engagement (of all organizations) at the location. When there is overlap or competition, an organization's share of appeal is given by the proportional engagement: $E(t,a,x)/\sum_a E(t,a,x)$. So, actual appeal is this share applied to the resource level of a location, or in formal terms: $R(t,a,x)[E(t,a,x)]/\sum_a E(t,x)$. Figure 3 illustrates how actual appeal works in the modeling framework; it shows the actual appeal of the two organizations represented in Fig. 2 by engagement when operating in the resource space of Fig. 1. Obviously, one organization (the leftmost part of the figure) appears as a specialist located in an abundant part of the space and the other as a generalist in sparser parts of the environment. Because they both engage at positions e and h and because resources are available there, they each show actual appeal at those positions, proportional to their engagements. The generalist also shows actual appeal at positions c, g and i.

Note that this formalization of competition and splitting of appeal at a given position has a specific property: if an organization is the only producer in a given position, then it will get all the appeal, no matter what size engagement budget it allocates to that position. This property of the model is realistic some situations, but less realistic in others. For the former, just think of a gas station that is the only place in a given isolated town—the model assumes that this gas station will obtain (nearly) all the demand for gas in that town even if it neglects its customers relative to activities of stations in other towns.[3] All in all, we make this assumption for two reasons: First, the model does not assume that the total market's demand will be fulfilled as well—that process is influenced by the *capacity* (in the model organizations fulfill demand only up to their capacity). Second, in most of our experimental designs of 10 niche positions and 40 organizations, lone niche occupants will be rare, and resources will be almost always contested.

3 The principle of allocation (PoA)

The PoA holds that a "constant-sum" constraint limits niche width in organizations. That is, increased niche width comes at the expense of lowered engagement at some positions (Péli 1997; Hsu 2006). The simplest version of this principle operates like a fixed budget—once some part of it is expended at some location, then not as much is available for deployment at other locations. In the model we use here, this simple version of PoA operates automatically through engagement, where each organization receives a fixed budget initially. Through the engagement process, an organization that locates solely at a single position and uses its full budget there will be able (in a resource-tight context) to out-compete an organization with a wider but overlapping niche (say 2–3 positions). This occurs because the wider niche organization must spend some of its engagement budget at the other positions and the result of the competition is determined by relative engagement expenditures.

Recent theory and research on PoA in identity-based setting suggest a different, even stronger process (Carroll and Swaminathan 2000; Baron 2004; Hsu 2006). It shows that organizations which span wide parts of the resource space not only suffer

[3] An anonymous reviewer called our attention to a different example: a situation where someone opens the first restaurant in a small town where people are unaccustomed to dining out (e.g., a rural Russian town in early 1990). In this case, we would still maintain the restaurant would (like the gas station above) get nearly all the demand in the town and could ignore restaurants in other towns. What seems different here is that we would expect that total demand in the town would grow after the first restaurant. That is, aggregate demand may be stimulated by supply. At this stage, we do not incorporate this complication into the model, but it could be done readily in an extension.

from thinly spread budgets but from disproportionately weaker identities, as well as audience penalties in some cases. In other words, some audiences may disfavor wide-niche organizations in principle (typically for moral or signaling reasons) or there may be non-linear positive returns to engagement at some positions. For example, Microsoft may enter the gaming market but it will not develop much of an identity as a gaming company due to its many other activities. So, engagements based on a wide niche may be penalized above and beyond the fixed budget constraint. Whereas the budget limitation makes it hard to span broad resource spaces in the fact of competition, a penalized engagement in such a situation makes it even harder. In economic terms, the penalized engagement amounts to a scope disadvantage.

In the analysis we conduct here, what we call the PoA is modeled with this identity-based process in mind. In setting PoA conditions, we let the market or audience penalize broad niche organizations by discounting the engagements of the organization in positions that are not the organizations' focus. A strong PoA in our setup means a bigger discount factor for the engagement. It is important to recognize that our low-PoA condition still contains the fixed budget constraint on engagement that is sometimes called PoA.

3.1 Operationalization of the principle of allocation

In the analysis we conduct here, PoA is modeled by reducing an organization's engagement when its niche width spans many social positions. In other words, in setting PoA we let the market or audience penalize broad niche organizations by shrinking their engagement budgets.

More specifically, in each period t for each organization a at each resource position x, we force engagement to be reduced with the inverse proportion of the engagement at that position of the organization and the total engagement of the organization. To model this effect, we use the function: $E_{(t,a,x)} = E(t,a,x)\left(\frac{E(t,a,x)}{\sum_x E(t,a,x)}\right)^A$. The parameter A regulates the strength of the PoA penalty. Positive values of A lead to a scope disadvantage, a key implication of the PoA. If $A = 0$, then there is no penalty, and higher values of A reflect stronger PoA processes. Reduced engagement feeds back to the model of competition, inasmuch as the resources in each resource position are distributed to the organizations proportional to their now-reduced engagements.

4 Scale advantage

A scale advantage exists when the returns to some activity increase disproportionately with the scale at which it is conducted. The most familiar case comes from an activity that incurs both a fixed cost, independent of the number of items produced, and a variable (per-item) cost. The marginal cost of producing an item in this case declines with scale, as the ratio of fixed to variable costs declines. Organizations generally use scale advantages to improve the price/quality of offerings relative to those of competitors.

Here we follow Hannan et al. (2007) in translating the scale advantage idea to mean that growth in scale gets converted into greater engagement—a rise in scale inflates an organization's appeal distribution by increasing its expected level of total engagement. Note that scale advantage conceptualized this way overrides the part of the principle of allocation that holds that the expected level of total engagement does not vary among the producers in a market.

4.1 Operationalization of scale advantage

We set $\overline{S}(t)$ as the mean size of all organizations a at time t. Then if $S(t,a) > \overline{S}(t)$, we model scale advantage as given by $\left(\frac{S(t,a)}{\overline{S}(t)}\right)^Q$, where Q is simply a scaling factor; there is no scale advantage if $S(t,a) < \overline{S}(t)$.

In this operationalization, scale advantage is relative. While we could have modeled SA as an absolute measure, such as a direct function of organizational size, we chose not to do this because the competitive advantage offered by scale is not absolute but relative to competitors. In the most common interpretation, scale provides cost advantages and these matter if another firm is larger or smaller, and to what degree. The operationalization also assumes for modeling simplicity that scale advantage never reaches any limit: larger organizations always possess advantage over smaller ones. Of course, in some real contexts, the advantages of very large scale are thought to taper off as complexity and inertia impede coordination.

5 Building the model of organizational evolution

To examine how SA and PoA affect the distribution of organizational sizes and niche widths, we constructed a more complete model of organizational evolution. The minimal additional components for such a model include capacity, size, and niche expansion.

5.1 Capacity

Every organization possesses a production capacity at any given point in time. The capacity represents the total amount of goods or service that it is able to produce according to the existing facilities, labor, capital etc. The capacity C of organization a at time t is given by $C(t,a)$ variable, which evolves initially as a Gibrat process, determined exogenously by random draws (Sutton 1997). Increments in capacity are determined in part by the relationship between capacity and the amount of resources the organization could obtain after competition. If the capacity is smaller than the possible share the organization could obtain, then capacity grows according to a Gibrat with a high-growth parameter. If capacity already exceeds demand, then capacity changes according to a Gibrat of lower expected value. Formally, the algorithm is:

$$\begin{aligned}
&C(t+1,a,x) = C(t,a,x)\cdot \exp(0.1 + \mathit{RNormal}\cdot 0.15)\\
&\quad \text{if } C(t,a,x) < \sum [E(t,a,x)/E^*]R(x) \quad \text{and}\\
&C(t+1,a,x) = C(t,a,x)\cdot \exp(0.02 + \mathit{RNormal}\cdot 0.15) \quad \text{otherwise}
\end{aligned}$$

where *RNormal* is a random normal deviate.

5.2 Organizational size

In this analysis, we consider organizational size as the main outcome of interest. As we have set up the model, size reflects the outcome of processes of resource acquisition and competition. Organizations take resources from their positions in the environment based on (1) whether they have the capacity to serve the positions and (2) whether they can out-compete other organizations attempting to draw resources at the same positions. The outcome is the size of the organization, as represented by its total goods or services sold. Size must always be less than or equal to an organization's capacity. Unused capacity plays no active role in triggering competition in the model, as it sometimes does in real industrial contexts.

At every social position x, there will be a competition for resources $R(x)$ if several organizations are located there and have available capacity. If enough resources are available at position x [that is, if $R(x)$ is large enough] for all organizations seeking resources to fill capacity, then each takes what it needs. That is, if $R(x)$ is greater than all $C(t, a, x)$ summed over x, then all a organizations achieve the size determined by their capacities.

Let organizational size be construed as capacity realized in the environment, in the sense of the number of resource units the organization is able to take from the environment. Let it be the case that size at time t for organization a at position x is given by $S(t, a, x)$. The upper bound on $S(t, a, x)$ is given by capacity $C(t, a, x)$.

If $R(x)$ is less than all $C(t, a, x)$ summed over x, then organizations are involved in a competition for scarce resources at position x. The outcome of the competition depends on the relative efforts spent by the organizations located at that position, which is given by their engagements $E(t, a, x)$. Let the sum of these $E(t, a, x)$ values at t over all the organizations present at x be noted by E^*. Then the outcome of the competition is given by $[E(t, a, x)/E^*]R(x)$ so long as it remains below $C(t, a, x)$ and $C(t, a, x)$ otherwise. That is, the size of organization a at x is given by

$$S(t, a, x) = [E(t, a, x)/E^*]R(x) \quad \text{if } C(t, a, x) > \sum[E(t, a, x)/E^*]R(x) \quad \text{and}$$

$$S(t, a, x) = C(t, a, x) \quad \text{otherwise.}$$

5.3 Engagement allocation and niche expansion

As explained above, at the end of each time period every organization is assigned a new engagement budget (which is a function of its size in the previous period). The increment to an organization's engagement budget is allocated either to its existing positions or to a new environmental position taken by the organization. If applied to existing positions, then the engagement budget is allocated across all existing positions, proportionally to the engagement levels at the previous period at the positions. So, for instance, if the increment is 0.2 and the organization operates equally in two positions, then each position's engagement is 0.1. Note that in this case the relative distribution of the engagement budget of an organization does not shift.

An organization that gets an increment to its engagement budget might use it to expand its niche width. We model such expansion as a random occurrence. Let *NExp* be the probability of a niche expansion. Then any organization with an increment to

Structure of a simulation run

0^{th} period: Initial values of the parameters are set

- Number of organizations
- Number of resource positions
- Resource distribution
- Number of periods in the simulation run
- Parameters for the Gibrat growth process
- PoA intensity
- SA intensity
- Probability an organization might expand
- Each organization is allocated an initial engagement budget of 1, which it allocates to a randomly chosen resource position.

In each period (listed in the order the steps take place)

1. Competition takes places. In each position, the available resources are divided among the organizations that are present. The resources are divided proportionally to the engagements, as discounted by PoA.

2. The organizations fulfill the demand they gained in step 1, up to their capacity. The size of the organization in the time period is defined as the total fulfilled demand.

3. According to its relative position in the size distribution, each organization is assigned a new engagement budget (this process is governed by SA)

4. Each organization allocates its new engagement budget across the positions: it either (1) allocates the new engagement budget across positions it already occupies, allocating the engagement proportional to the allocation in previous period, or (2) if the engagement budget increases, the organization may enter a new position, in which case all the increase in the engagement budget is allocated to this new position.

Fig. 4 Overview of the computational model

its engagement budget experiences the risk *NExp* of expanding. The location of the expansion is also random, with an equal chance that it occurs at any of the organization's currently unoccupied positions.

Of course, this simple operationalization of engagement allocation and niche expansion can be elaborated in subsequent research. For example, engagement allocation in this model does not depend on the (possible) gains of allocating engagements to a given niche. However, as our main focus in this model is not on the organizational level but on the population level, we decided to keep the modeling of organizational action simple. A similar rationale applies to our implicit assumption that organizations might grow indefinitely.

5.4 Model overview

Figure 4 provides an overview of the operation of the simulation model. Initially, at time 0 the environmental resource distribution is set. In the next time period, time 1, the levels of engagement (E) and capacity (C) are assigned to each organization, as explained above. The resulting competition with other organizations at each resource position determines the organization's size in that period. In the next period, time 2, and all subsequent periods, engagement is recalculated based on prior size. So too is capacity, although its evolution is governed by the Gibrat mechanism. Finally, although not shown, expanding organizations undergo some chance of niche expansion in the subsequent time period.

5.5 Model evaluation

In assessing the model's basic validity, we examine its ability to meet three general expectations of previous theory and research: (1) Under a strong PoA process and no SA, narrow-niche organizations should eventually dominate the population; (2) Under a strong SA process and no PoA, large organizations should eventually dominate the population; (3) Under the operation of both PoA and SA, a tradeoff should sometimes be observable for long periods. By strong process, we mean one where the parameter settings are set to levels that produce pronounced effects (we also at points refer to PoA and SA parameters as low or high to reflect varying intensity of effects). We acknowledge that the values for the parameters we used in the models are stylized, and when we refer to them as low or high or strong, we mean low or high in the parameter space explored in our models. As the model is stylized, we do not want to (and cannot) establish direct relations to given empirical settings. However, we believe that such a modeling exercise should be viewed as a "proof of concept," which explores new phenomena. For instance, a strong SA process should allow some organizations to potentially overcome the PoA, thereby generating a dual structure (consisting of either a plethora of wide and narrow niche structures or a combination of large and small sized organizations) in a population. In scoring the model's performance on these conditions, we investigate evolution over time as well as the equilibrium distributions.

6 Findings

We organize the findings of the simulations into three major parts. The first part describes some basic results for the model, and discusses the tradeoff between SA and PoA, including how these processes influence the emerging market structures. In the second part, we conduct sensitivity analyses, and investigate under what circumstances the relationships hold. Specifically, we analyze the effect of the shape of the resource distribution, and investigate how the effects of SA and PoA change over time. Finally, we focus our analysis on the organizational level, and investigate the optimal behavior of organizations under different SA and PoA setups.

6.1 Scale advantage and principle of allocation

According to our basic expectations for the model's validity, we want to see (1) that as the SA process gets stronger, a few large, generalist organizations begin to dominate the population and (2) that as PoA gets stronger, small and focused organizations should start to proliferate. Combining these two forces, we expect to see that dual structures will emerge in markets where both SA and PoA operate with force. To examine these expectations, we look at two different measures of market

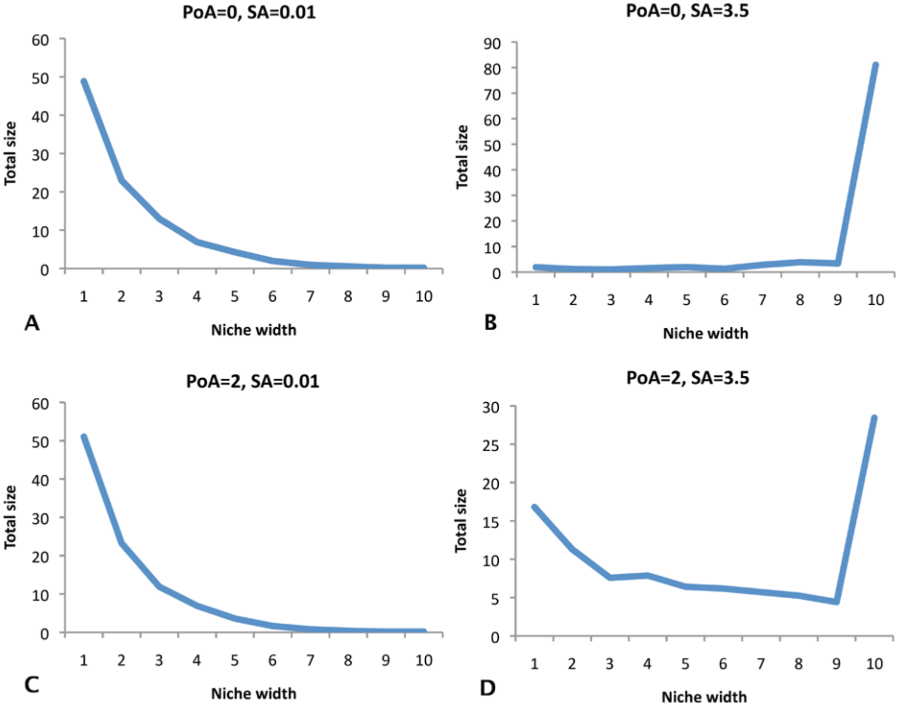


Fig. 5 Aggregate size of organizations by niche width, in four different SA/PoA settings

structure outcomes. First, we investigate the aggregate size of organizations by niche width. This measure allows us to assess what proportion of total resources accrues to narrow-niche and broad-niche organizations. Second, we look at the size distribution of organizations, as measured by (1) concentration (measured with the Gini index) and (2) polarization, measured using Wolfson's (1994) p^*—see Appendix for a description). Polarization allows us to identify the emergence of dual market structures. The various measures provide different perspectives on the niche width distributions and size distributions of the simulated organizations.

Our simulation experiments varied the SA parameter Q from 0, 1, 2, ..., to 8; the PoA parameter A ranged from 0, 0.2, 0.4, ..., to 2.0. For clarity in isolating effects of SA and PoA, we kept all other parameters fixed. Specifically, we assumed 10 market positions in the environment, each with a resource level of 10—this setup implies that the resource space is uniformly distributed. The simulations started with 40 organizations, all with an initial size of 1, an initial capacity of 1, and an initial engagement budget of 1. Each organization started with a narrow niche, NW = 1, located in a randomly chosen position. Each organization was assigned a certain probability that it expanded its niche width if it grows in size—these probabilities were drawn randomly from a 0–0.3 uniform random distribution. Each simulation run was 100 periods, and each setup was iterated 500 times.

Figure 5 shows how the average aggregate size of organizations changes by niche width under four different SA and PoA settings. Figure 5a provides the baseline case,

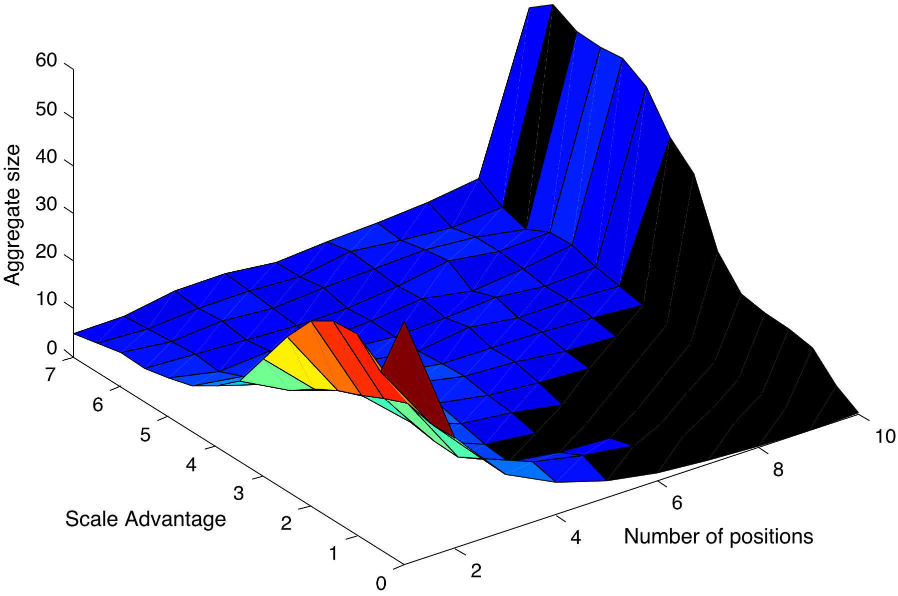


Fig. 6 Aggregate size of organizations by niche width, by SA

in which neither SA nor PoA operates. Figure 5b shows that strong SA (and no PoA) leads to the dominance of generalist organizations. Figure 5c illustrates that strong PoA leads to more narrow-niche organizations, although the resulting distribution does not differ radically from the baseline case, Fig. 5a.[4] Figure 5d shows that in setups with both strong SA and strong PoA, a dual market structure emerges: a larger part of the resource space is taken up by either narrow or wide niche organizations. These figures provide evidence supporting the validity of the model.

To check the robustness of the PoA and SA effects, we ran simulations with a range of PoA and SA settings. Figure 6 provides one of these validity checks—it shows how change in the SA parameter Q affects the average aggregate size of organizations by niche width (keeping the PoA parameter A constant, at 2). This figure illustrates the trade-off between SA and PoA. When SA is weak and only PoA operates, then the market is dominated by focused, narrow niche width organizations. As SA gets stronger, dual market structures emerge. And, as SA gets very strong, the dual market structure disappears, and the market becomes dominated by wide niche generalists. This finding reveals a scope condition for resource partitioning: for a bifurcated market structure to arise, SA cannot be too strong relative to PoA. In other words, a polarized market only arises if the "right" combinations of PoA and SA are present: both PoA and SA need to be operative, but neither of them can be too dominant.

[4]The reason for this is the following: if there is no scale advantage, organizations do not really grow in size (and therefore in engagement budget). Thus, there will be only small amounts of engagement in the positions into which they expand, and therefore PoA does not really make much of a difference.

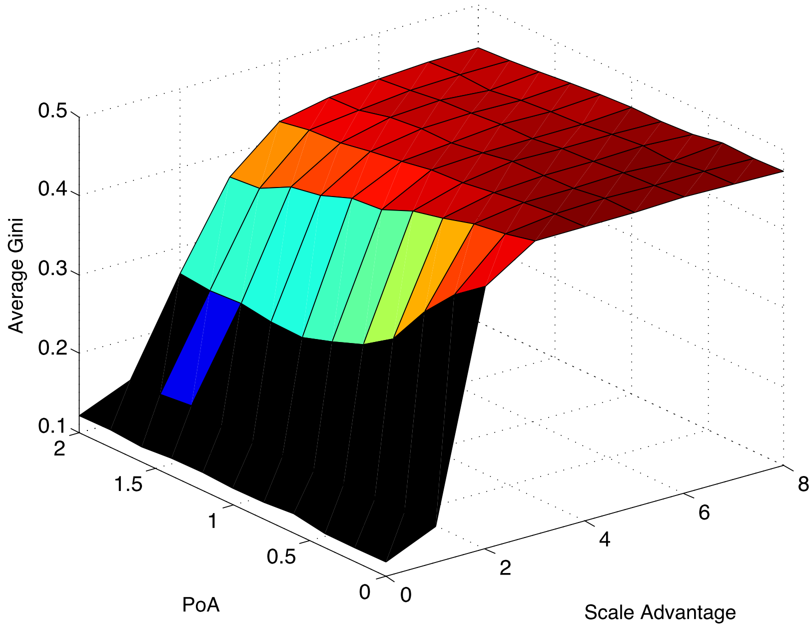


Fig. 7 Average Gini score by SA and PoA

Our basic expectations for the model's validity concern both niche width and size distributions in different setups. An advantage of the computational model is that it allows us to disentangle the effects of size (small or large) from niche width (narrow specialist or wide generalist). So, we next investigate the effect of PoA and SA on the size distribution of organizations in concentration (measured with the Gini coefficient), and polarization (measured with Wolfson's (1994) polarization measure; see Appendix for a short description of this measure).

First we analyze the steady-state values of concentration and polarization. We calculated the Gini and Wolfson's p^* measures after 100 periods (the process always reached the steady state within 100 periods).

Figure 7 shows how the average Gini coefficient of concentration in organizational size changes with levels of SA and PoA, across all the simulation runs. As expected, the average Gini increases with SA. Also, as expected, the average Gini decreases with PoA, even though its effect is apparent only for moderate levels of SA.

Figure 8 shows the average values of the polarization measure across different levels of PoA and SA. Basically, it demonstrates that (1) when SA is very strong or very weak, the emerging size distribution is not polarized, (2) when PoA becomes stronger, the size distribution becomes more polarized. An alternative way of stating these findings: for each level of PoA, the SA has an inverse U-shape effect on polarization. When SA is weak, small organizations proliferate; and when SA is strong, a few large organizations eventually dominate. But at intermediate levels of SA, polarized or dual market structures emerge.

To cross-validate the p^* measure as an indicator of market polarization and resource partitioning, we also conducted a different kind of test. Resource partitioning

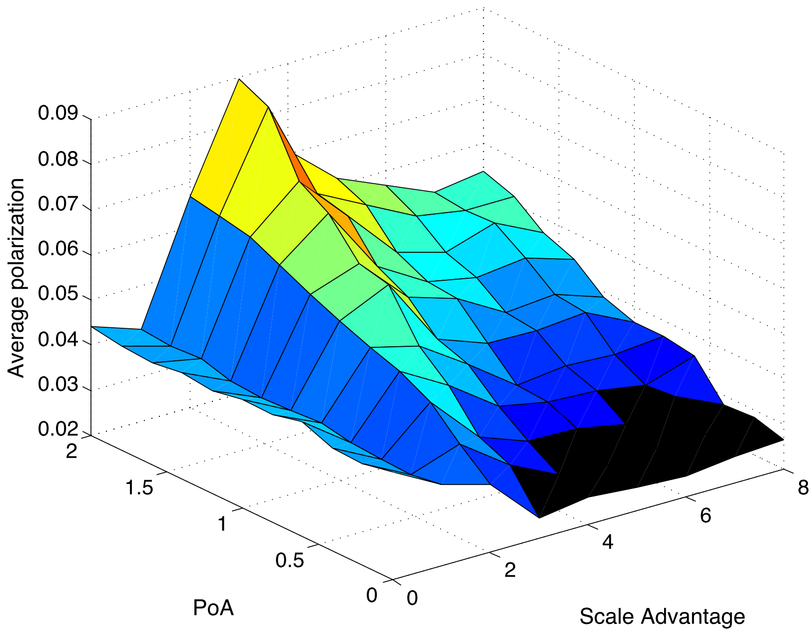


Fig. 8 Average polarization score by SA and PoA

theory asserts that in markets where partitioning took place, there will be a competitive separation between organizations with wide niche width and small niche width. To test whether high values of p^* pick up this separation, we conducted the following test. At the end of each simulation run (at 100 period), for all organization dyads (i.e., $40^*39/2 = 7{,}800$ dyads), we calculated whether the two organizations have an overlap in their niches (direct competition). Then, we run logistic regressions to estimate how the niche widths of organizations affect whether they compete in different p^* outcomes. We found (results not shown here) that in markets with high p^*, the level of cross-competition between narrow- and wide-niche width organizations is much lower than it is in low p^* markets. This finding is in accordance with the prediction of resource partitioning theory.

To assess precisely the effects of SA and PoA levels on concentration and polarization across the runs, we estimated linear regressions. This is what Law and Kelton (2000) call a "metamodel" of the simulation. It simplifies by using linear regression but allows for the simultaneous inclusion of many factors. As Figs. 7 and 8 illustrate, the effects of PoA and SA on concentration and polarization are non-monotonic, so we also include the quadratic forms of PoA and SA values. Also, because both our theory and Figs. 7 and 8 suggest dependence between the effects of PoA and SA, we include their linear and quadratic interaction terms.

It is perhaps important to emphasize that the coefficient estimates of the regression models force the effects of PoA and SA on concentration and polarization (already shown in Figs. 7 and 8) to operate through the specified regression equation. Although linear and quadratic regressions likely oversimplify the relationships shown in Fig. 7 and 8, we find them helpful for understanding what is going on because as the number of parameters increase, graphs are not tractable any more. That is, we use these functional forms as simplifications to summarize possibly complicated results rather than as any precise specification of underlying causal relationships.

Table 1 shows the estimated linear regression coefficients for concentration (Gini) and polarization (p^*) on the SA and PoA settings, respectively (the simulation setup is the same that is described above). Basically, all the estimated effects are in line with expectations for the model's validity. Higher PoA depresses concentration, and higher SA increases it. The interaction effect of PoA and SA is negative, indicating that when SA is strong, the negative effect of PoA amplifies (i.e., becomes more negative). This condition gives rise to the possibility of polarization.

The second column of Table 1 shows the coefficients on polarization. We also find this regression instructive: while both SA and PoA exert negative main effects on polarization, the interaction effect between PoA and SA drives the polarization measure (keep in mind that the values of PoA range between 0 and 2, and the values of SA range between 0 and 8). The strong positive interaction effect shows that the emerging size distribution tends to become polarized as both PoA and SA strengthen. The parameter estimates are in accordance with the results of Figs. 7 and 8.

To check the robustness of the above results, we conducted thorough sensitivity analyses on the initial parameters, specifically varying the number of organizations, the size of the resource space, and the initial size of the engagement budget (this is where relying on regressions becomes necessary: it would be very cumbersome to create a graph for each parameter combination). We reanalyzed the effect of PoA and SA on concentration and polarization (see Table 1) under various initial conditions.

Table 1 Regression estimates of effects of SA and PoA on Gini and polarization

	Gini	Polarization
PoA (A)	-0.0224^{***}	-0.0086^{***}
	(0.0028)	(0.0013)
PoA^2 (A^2)	0.0001	0.0065^{***}
	(0.001)	(0.0005)
SA (Q)	0.1312^{***}	-0.0021^{***}
	(0.0007)	(0.0003)
SA^2 (Q^2)	-0.0109^{***}	-0.0001^{***}
	(0.0000)	(0.0000)
PoA × SA ($A \times Q$)	-0.0046^{***}	0.0056^{***}
	(0.0005)	(0.0001)
PoA^2 × SA^2 ($A^2 \times Q^2$)	0.0003^{***}	-0.0003^{***}
	(0.000)	(0.0001)
Constant	0.1142^{***}	0.0426^{***}
	(0.0016)	(0.0008)
R^2	0.8934	0.2236
$N = 19{,}800$		

$^{***}p < 0.01$

Table 2 Sensitivity analysis of varying initial conditions

	Gini	Polarization
PoA (A)	-0.0164^{***}	-0.0056^{***}
	(0.0009)	(0.0005)
PoA^2 (A^2)	0.0028^{***}	0.0064^{***}
	(0.0004)	(0.0002)
SA (Q)	0.1238^{***}	0.0027^{***}
	(0.0002)	(0.0000)
SA^2 (Q^2)	-0.0096^{***}	-0.0008^{***}
	(0.0000)	(0.0000)
PoA × SA ($A \times Q$)	-0.0094^{***}	0.0078^{***}
	(0.0001)	(0.0001)
PoA^2 × SA^2 ($A^2 \times Q^2$)	0.0004^{***}	-0.0003^{***}
	(0.0001)	(0.0001)
Number of organizations	0.0012^{***}	-0.0007^{***}
	(0.0000)	(0.000)
Initial engagement budget	-0.0126^{***}	0.0043^{***}
	(0.0000)	(0.0001)
Number of market positions	-0.0029^{***}	0.0026^{***}
	(0.0000)	(0.000)
Constant	0.1082^{***}	0.0355^{***}
	(0.0008)	(0.0004)
R^2	0.8654	0.3988
$N = 196{,}020$		

$^{***}p < 0.01$

Table 2 shows the estimated linear regression on Gini and p^*, such as in Table 1, but now with including various levels of the number of organizations (varied between $20, 25, \ldots, 60$); the number of resource positions (varied between $5, 6, \ldots, 15$), and the initial size of the engagement budget (0.5, 1, 1.5, 2). The estimates show clearly that although the initial conditions influence the concentration and the polarization of the market, the main effects of PoA and SA on concentration and polarization do not change appreciably.

6.2 Evolution of Gini and polarization

The above analysis shows how SA and PoA influence the equilibrium market structure. Now we investigate how concentration and polarization evolve over time in the four PoA/SA setups shown in Fig. 5. The other parameters remain fixed, as above.

We compare the four cases: (1) no SA, no PoA; (2) no SA, strong PoA; (3) strong SA, no PoA; and (4) strong SA, strong PoA. The first case, no SA-no PoA, describes our baseline case, in which organizations' sizes change more or less randomly, and we only expect a slight increase of Gini and polarization over time (due to the Gibrat

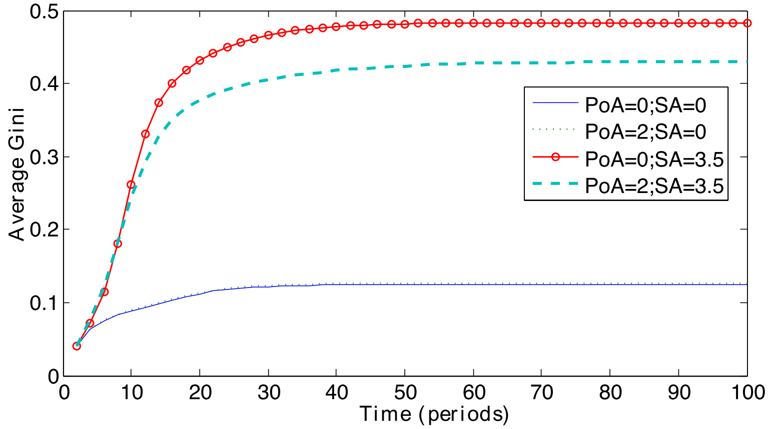


Fig. 9 Average Gini score over time for various SA/PoA settings

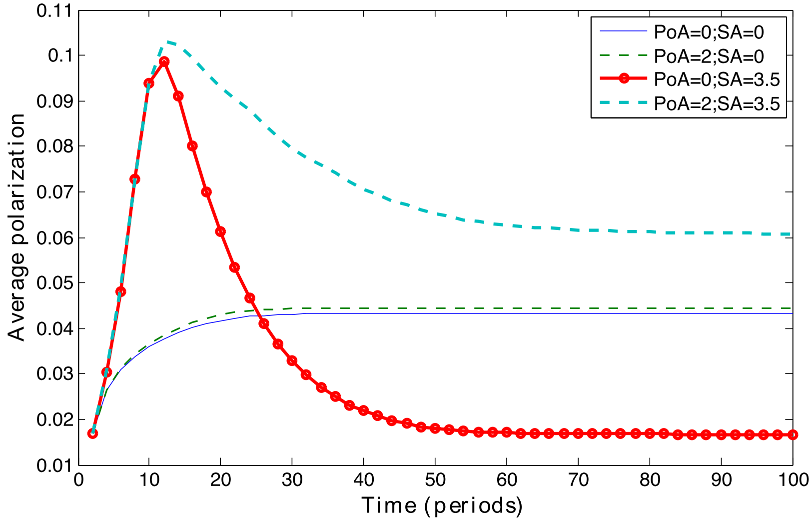


Fig. 10 Average polarization over time for various SA/PoA settings

growth process). The second case, no SA–strong PoA applies to populations where focus constitutes an advantage. Here we expect concentration to remain low. The third case, strong SA–no PoA is the classic scale advantage setup, where we expect the large organizations to dominate eventually. Therefore, we expect the Gini-index to increase over time, and the polarization measure to decrease over time. The fourth case, strong SA–strong PoA, is the balanced setup where we expect dual market structures to emerge. Figures 9 and 10, respectively, show the evolution of the average Gini and polarization over time.

Figure 9 shows that concentration (Gini) increases over time in all setups but dramatically so when SA is strong. Clearly, SA operates as expected. Interestingly, PoA only has a discernible effect on the Gini index in cases where SA is strong (this is consistent with our earlier findings on the equilibrium effects of SA and PoA).

Figure 10 reveals substantial differences in the temporal patterns of polarization for the different cases. With no SA, polarization increases gradually. With strong SA, however, a strong non-monotonic pattern appears: in the earlier periods polarization increases sharply, after which it decreases slowly to an equilibrium level. In these strong SA cases, PoA exerts a strong effect on the polarization measure: in cases in which PoA is strong, polarization stabilizes at a relatively high level, indicating dual market structures. Without PoA, however, polarization drops back relatively fast, indicating a highly concentrated size distribution.

Why do the strong SA cases produce this non-monotonic pattern in the evolution of the polarization measure? Our investigations into the specifics of simulated trajectories suggest the following scenario. In the early phase of the process, organizations are small and the system contains excess demand. That is, each organization can freely grow without being constrained by competition. In conditions with no SA, the organizations grow at more or less the same speed, resulting in a relatively slow and gradual increases in concentration and polarization (given that in the initial condition each organization is of the same size, any variance in size results in increase in the concentration and polarization). Around the 10–12th period,[5] however, organizations develop enough capacity to satisfy all the demand and competition begins driving the process through the differences in engagement. In the no SA cases, organizations have the same level of engagement, and the process and the size distribution stabilizes. In the strong SA cases, the size distribution gets less polarized after the initial periods, but this decrease corresponds to two different underlying size distributions. In the strong PoA case, a dual market structure emerges, with a few large organizations and larger number of small organizations, yielding high polarization and relatively high concentration. In the no PoA case, however, the market will be populated by a small number of large organizations, thus generating the lower equilibrium polarization and high concentration.

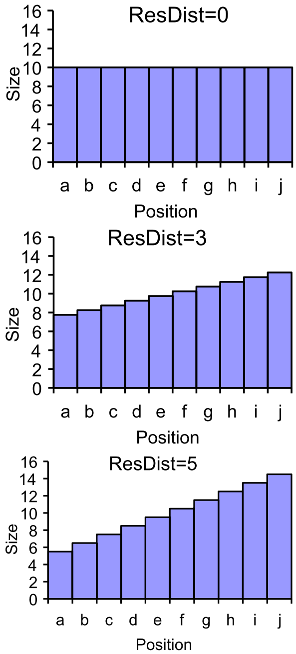
The evolution of niche widths and organizational sizes are also worth mentioning. In our simulations, the aggregate size of simulated organizations increases monotonically over time: in the beginning of the simulations, organizations do not have enough capacity to fulfill all the demand, and their aggregate size increases as organizations increase their capacity, eventually fulfilling all the possible demand (which is a stable state in our simulations). The evolution of the average niche widths has a similar monotone increasing trajectory (this is an automatic consequence of the model, which does not permit niche contraction).

6.3 Resource distribution shape

How does the distribution of the resource space influence the organizational size distribution? In general, organizational ecology leads us to expect that the more concentrated the resource space is, the more concentrated the emerging size distribution

[5] Obviously, the exact timing depends on the other parameters of the model.

Fig. 11 Illustrative different values of *ResDist*



of organizations will be (Boone et al. 2002). Also, resource partitioning theory postulates that if we find the conditions of (1) strong PoA, (2) strong SA, and (3) a concentrated resource distribution, then the emerging size distribution will be polarized.[6] A basic idea is that when large organizations venture into market positions with scarce resources, they lose more from the PoA than they gain from increasing SA. We have seen above that polarized market structures can emerge even if the resource space is uniformly distributed. In this section, we study how the effects of PoA and SA change with increasingly concentrated resource distribution. We did so by reconfiguring the environmental resource distribution in the simulation. We introduce a variable, *ResDist*, that determines to what extent the resource distribution diverges from uniform. In our model, *ResDist* can be viewed as a slope in the ranking of positions. See Fig. 11 for an illustration (but recall that the visual ordering of positions shown here does not matter). If *ResDist* is high, resources are concentrated and the tastes are rather homogeneous; if *ResDist* is low, resources are spread more evenly across positions and tastes are heterogeneous.

As in Tables 1 and 2, we estimated linear regressions to investigate how the concentration of the resource distribution affects the emerging polarization and concentration of organizational sizes. Table 3 shows the regression estimates of equilibrium polarization and concentration on the SA (Q), PoA (A) and *ResDist* settings for the simulation. The initial parameter values are as before, and *ResDist* varies between 0

[6]Several other important assumptions are made in resource partitioning theory to generate this prediction, namely, that (1) the dimensions of the resource space are ordered; and (2) the overall shape of the resource distribution is unimodal.

Table 3 Regression estimates of effects of concentration in resource distribution (*ResDist*) on bifurcation

	Gini	Polarization
PoA (A)	-0.0266^{***}	-0.0102^{***}
	(0.0006)	(0.0002)
PoA^2 (A^2)	0.0003	0.0087^{***}
	(0.0002)	(0.0004)
SA (Q)	0.1574^{***}	-0.0081^{***}
	(0.0002)	(0.0000)
SA^2 (Q^2)	-0.0145^{***}	0.0004^{***}
	(0.0000)	(0.0000)
PoA × SA ($A \times Q$)	-0.0039^{***}	0.0056^{***}
	(0.0003)	(0.0000)
PoA^2 × SA^2 ($A^2 \times Q^2$)	0.0004^{***}	-0.0004^{***}
	(0.000)	(0.0000)
ResDist	0.0052^{***}	0.0021^{***}
	(0.0001)	(0.0000)
$A \times$ *ResDist*	0.0012^{***}	-0.0006^{**}
	(0.0001)	(0.0000)
$Q \times$ *ResDist*	-0.0011^{***}	-0.0004^{***}
	(0.000)	(0.0000)
$A \times Q \times$ *ResDist*	-0.0002^{***}	0.0000^{***}
	(0.000)	(0.0000)
Constant	0.0950^{***}	0.0444^{***}
	(0.0005)	(0.0001)
R^2	0.9029	0.3941
$N = 4{,}125{,}500$		

Note: Higher values of *ResDist* indicate more concentrated resource spaces

$^{**}p < 0.05$, $^{***}p < 0.01$

and 8. Beside the main effect of resource distribution (*ResDist),* we included interactions with PoA and SA to explore how the effect of PoA and SA changes across different resource distributions.

First, note that the main effects of SA and PoA from above hold across different levels of resource space concentration. Second, note that the main effect of concentration in the resource space agrees with expectations: more concentrated resource space leads to organizational size distributions that are both more concentrated and more polarized. Third, the interaction variables between resource space concentration and PoA and SA are interesting. For the Gini, the negative coefficient of the interaction with SA shows that in concentrated resource spaces, SA is less important; the positive coefficient of the interaction with PoA shows that the effect of PoA is weaker in concentrated resource spaces (this finding is not surprising either). For polarization: the interaction between concentration of resource distribution and SA is negative, i.e., in runs with concentrated resource space, stronger scale advantage leads to lower polarization. This finding confirms the new scope condition for Resource Partitioning we

Table 4 Regression estimates of effects of niche expansion on $\ln(\text{Size}_{t+1}/\text{Size}_t)$

	Model 1 $\ln(\text{Size}_{t+1}/\text{Size}_t)$	Model 2 $\ln(\text{Size}_{t+1}/\text{Size}_t)$	Model 3 $\ln(\text{Size}_{t+1}/\text{Size}_t)$
$\Delta NW_{t,t+1}$	-0.044^{***}	-0.128^{***}	-0.211^{***}
	(0.015)	(0.028)	(0.040)
NW_t		-0.002^{**}	-0.009^{***}
		(0.001)	(0.001)
$\Delta NW_{t,t+1} \times NW_t$		0.026^{***}	0.032^{**}
		(0.007)	(0.013)
Size_t			0.002^{***}
			(0.000)
$\Delta NW_{t,t+1} \times \text{Size}_t$			0.016^{***}
			(0.004)
$\Delta NW_{t,t+1} \times NW_t \times \text{Size}_t$			-0.002^{***}
			(0.000)
Constant	-0.016^{***}	-0.013^{***}	-0.007^{***}
	(0.001)	(0.002)	(0.002)
N	39,600	39,600	39,600
R^2	0.0002	0.0006	(0.003)

Note: Observations of size = 0 are excluded
$^{**}p < 0.05$, $^{***}p < 0.01$

identified before: too high SA leads to too high concentration, so polarization cannot take place.

6.4 Organizational strategy

Here we turn our focus to the organizational level, and ask what might be good strategies for organizations under various environmental conditions. More specifically, we ask: When is it beneficial for an organization to increase its niche width? To explore this question, we assign different niche expansion parameters to the organizations in each setup, and observe how the organizations' sizes change when entering a new position.

In the simulations we show below, we assumed a uniform resource distribution, with PoA parameter $A = 2$ and SA parameter $Q = 3.5$. While in the previous analyses we investigated macro level properties of the system (concentration and polarization), here we expect that the two advantaged strategies (being focused or being large) will emerge from the organizational level estimates as well.

To investigate the success of various strategies, we rely on linear regression. We use linear regressions, because regressions allow us to investigate the effect of multiple variables (while graphs can only show the relationship between two or three variables at a given time). Table 4 contains three regression estimates on the size changes after entering a new position. Consistent with growth models typically estimated from empirical data, the dependent variable is $\ln(\text{Size}_{t+1}/\text{Size}_t)$. In the regression, each organization-time period comprises an observation. After excluding organizations with zero size, the simulation data yield 39,600 observations. The regression compares size change when the organization enters a new position ($\Delta NW_{t,t+1} = 1$) with outcomes when (under similar conditions) it does not enter a new position ($\Delta NW_{t,t+1} = 0$). We also include control variables for the organization's niche width (NW_t) at t (Model 2), and the size of the organization at t (Model 3).

The results are in line with our expectations: entering a new position leads to a decrease in size. This reflects the force of the PoA. The interaction coefficient with previous niche width is also positive, however, indicating that entering new positions is beneficial for already-existing generalist organizations (niche width of six or more). Even stronger is the interaction coefficient with size: this shows that it is better for organizations already of a relatively large (size of 4 or more in this setup) to increase niche width.

The above analysis shows that the two stable states for organizations in either a strong SA or a strong PoA environment is to be, respectively, small and focused, or large and generalist. It also provides some insight into why generalists exist at all: if an organization occupies one position and it is of small size, it is better off in the short term not to enter new positions. This situation, the above analysis suggests, can only be overcome if the organization can grow large enough in its original position.

Because the dependent variable is non-linear, to ensure that we correctly interpreted the interaction variables (Hoetker 2007), we plotted the predicted effects of the main variables and their interactions. The plots (not shown here), confirm the effects of the interactions described above.

7 Ordered positions in resource space

So far we have considered only unordered resource positions. In this section, we introduce a distance measure to the social space, because in various settings the resource space is ordered along meaningful social dimensions such as age, education, or geographical location. Our question here is the following: Does the ordering of positions or categories change the major findings?

We incorporate ordering in the following way. We array the positions linearly and assume unit distance. So, the distance between two categories equals the difference between their positions. For example, the distance between categories 5 and 7 is 2, and we call two positions or categories neighboring if their distance is 1.

What processes does category ordering change? With ordered categories, the PoA process changes. According to the PoA, category crossing is detrimental because membership in different categories confuses members of the audience, causing them to question a spanner's identities (Hsu 2006). Therefore, we expect that the less similar the straddled categories are, the higher the punishment will be. To build in this operationalization of PoA, we change the discount factor audience members at each resource position apply to the organizations' local engagements. More specifically, in each period t each organization a at each resource position x,

$$E_{(t,a,x)} = E(t,a,x)\left(\frac{E(t,a,x)}{\sum_{i=1\ldots\text{Number\_of\_positions}} |i-x|E(t,a,i)}\right)^{A}$$

(compare this with the unordered operationalization of PoA in Sect. 3).

We first investigate how SA and PoA affect polarization and concentration in ordered categories. We reran the analysis presented in Table 1 with ordered categories. The results are quite similar to that of ordered categories: the signs and direction of the main variables are the same as for unordered categories, so we do not show them here. In short, the main result still holds: polarization can only be high if both PoA and SA are present, and they are not too strong.

Now we turn to analyze the micro level result: how does the category ordering affect optimal organizational action? For unordered categories, we find that in high PoA–high SA settings the main effect of niche expansion on size is negative, but it is positive for organizations that are already large. Here, in settings with ordered categories, we expect the same relationship to hold, but we also expect that wide niche is especially detrimental if there are gaps in it, i.e., in cases when organizations enter distant new niches, those that do not neighbor with positions they already occupy. To explore these questions, we observe how the organizations' sizes change when entering a new position. In the simulations we show below, we assumed a uniform resource distribution, with PoA parameter $A = 2$ and SA parameter $Q = 3.5$.

Table 5 shows three regression estimates on the size changes after entering a new position. In the regressions, each organization-time period comprises an observation. Consistent with growth models typically estimated from empirical data, the dependent variable is $\ln(\text{Size}_{t+1}/\text{Size}_t)$. After excluding organizations with zero size, the simulation data yield 118,000 observations. The regression compares size changes when the organization enters a new position that connects to already occupied positions ($\Delta NW_{t,t+1}$(entering neighboring position) $= 1$), when the organization enters a new position that does not connect to already occupied positions ($\Delta NW_{t,t+1}$(entering disconnected position) $= 1$), with outcomes when (under similar conditions) it does not enter a new position ($\Delta NW_{t,t+1} = 0$). Similarly to Table 4, we include controls for the size and niche width of the organization at time t.

The findings of Table 5 confirm our expectations: entering new positions is detrimental to growth. Moreover, growth is dampened more strongly if the new position does not connect to a position that is already occupied by the organization.

As above, because the dependent variable is non-linear, to ensure that we correctly interpreted the interaction variables (Hoetker 2007), we plotted the predicted effects of the main variables and their interactions. The plots (not shown here), confirm the effects of the interactions described above.

8 Discussion

We set out here to analyze the trade-off between the two major components of macro organizational behavior's niche theories, the Principle of Allocation (PoA) and Scale Advantage (SA). Adapting recent notions of audiences, resources, and the identity of organizations (Hannan et al. 2007), we built a computational model to analyze the

Table 5 Ordered categories: regression estimates of effects of niche expansion on $\ln(\mathrm{Size}_{t+1}/\mathrm{Size}_t)$

	Model 1 $\ln(\mathrm{Size}_{t+1}/\mathrm{Size}_t)$	Model 2 $\ln(\mathrm{Size}_{t+1}\mathrm{Size}_t)$	Model 3 $\ln(\mathrm{Size}_{t+1}\mathrm{Size}_t)$
$\Delta NW_{t,t+1}$(*entering neighboring positions*)	-0.041^{***}	-0.145^{***}	-0.150^{***}
	(0.012)	(0.025)	(0.025)
$\Delta NW_{t,t+1}$(*entering disconnected positions*)	-0.082^{***}	-0.202^{***}	-0.172^{***}
	(0.008)	(0.024)	(0.024)
NW_t		-0.004^{***}	-0.008^{***}
		(0.001)	(0.001)
$\Delta NW_{t,t+1}$(*entering neighboring positions*)		0.026^{***}	0.021^{***}
$\times NW_t$		(0.005)	(0.006)
$\Delta NW_{t,t+1}$(*entering disconnected positions*)		0.049^{***}	0.009
$\times NW_t$		(0.009)	(0.011)
Size_t			0.002^{***}
			(0.000)
$\Delta NW_{t,t+1}$(*entering neighboring positions*)			0.002
$\times \mathrm{Size}_t$			(0.001)
$\Delta NW_{t,t+1}$(*entering disconnected positions*)			-0.011^{***}
$\times \mathrm{Size}_t$			(0.002)
Constant	-0.011^{***}	-0.005^{**}	-0.003^{***}
	(0.001)	(0.001)	(0.001)
N	118,800	118,800	118,800
R^2	0.0008	0.0017	0.0040

Note: Observations of size = 0 are excluded
$^{**}p < 0.05$, $^{***}p < 0.01$

evolution of organizational populations under various environmental setups. In short, our model assumes that organizations face an audience. The members of the audience can be described by a multidimensional social space, and the positions of audience members in the space determine their tastes, resulting in a given distribution of demand across resource positions. According to the PoA, each organization possesses a given budget for engaging the audience, and distributes this engagement budget across the positions. SA is built into the model by relaxing the constant engagement assumption of PoA for larger organizations. Also, to model organizational evolution, we incorporated organizational capacity and niche expansion into our framework.

We first validated the model by showing that it reproduces three basic expectations for the "corner" solutions: (1) the dominance of large organizations in the strong SA setting, (2) the proliferation of narrow-niche and small organizations in the strong PoA setting, and (3) a dual market structure (based on either niche or size) when both SA and PoA are present.

The findings also correspond to our original expectation about the trade-off between PoA and SA: simulations show that in environments with strong PoA and SA, surviving organizations tend to be either large or focused (narrow-niche) to survive. So, on the population level, the combination of PoA and SA results in a dual market structure, as proposed by Carroll's (1985) theory of resource partitioning. It is noteworthy that we were able to do this here without incorporating processes of organizational entry and exit, empirical stalwarts of the resource partitioning research program. The model has thus extended the known implications of the theory by pushing it into a new domain.

The modeling results reveal an important scope condition for resource partitioning: the scale advantage cannot be too strong, because when SA is too strong it can overpower PoA and lead to a concentrated size distribution with low polarization. In other words, for any given level of PoA, SA has a non-monotonic effect, (1) if SA is very low or non-existent, the market will be fragmented, (2) if SA is strong but not too strong, polarization will take place (this is the resource partitioning situation), and (3) if SA is too strong, SA will overpower PoA and concentration will be high and polarization will be low. This scope condition has not been explicitly identified before in the literature, although some may say it is implicit in the typical distinction of generalists and specialists where only generalists are seen as evolving with scale advantages.

The above trade-off, however, is mediated by the resource distribution. Our findings regarding the main effect of concentration in the resource space agrees with expectations: more concentrated resource space leads to organizational size distributions that are both more concentrated and more polarized. This finding confirms the original assumption of resource partitioning theory that bifurcation takes place in a central-periphery resource distribution, but it shows that bifurcation can also happen in markets with less concentrated resource distributions (although the polarization here is weaker).

For organizational action, we aimed to identify circumstances under which specialists or generalist are favored, and we searched for cases where it is beneficial to increase niche width. Analyzing organizational action reinforced the population level results: under strong PoA and strong SA conditions, if an organization is small and focused, it is better off staying small and focused; on the other hand, if an organization is already relatively large or generalist, it is better off entering new positions.

Finally, we investigated whether the findings hold in resource spaces in which the resource positions are ordered. In order to do this, we modified our basic model so that it accommodates ordering in the resource space. Specifically, we built this ordering into PoA processes. Relying on previous literature, we asserted that the less similar the straddled categories are, the higher the punishment will be. We found that ordered categories and the modified PoA process does not change substantially the major relationships between SA and PoA, yielding the previously seen polarization and concentration of the organizational size and niche width distribution. We found, however, that category ordering does have important consequences for organizational action: when expanding, organizations are better off entering neighboring positions than entering disconnected positions.

8.1 Future research directions

In the computational model developed here, we relied on the Hannan et al. (2007) model of audiences, identity and competition; we tried to build a computational model that follows—and fleshes out in one particular way—the theory outlined in that book. The resulting model, however, might be modified profitably in many directions. In our view, a promising venture would aim to simplify the model, and by implementing other assumptions to try to come up with a model setup that can be solved analytically. This would provide a better grasp on the robustness of the findings—as simulations can never exhaust all possible parameter values.

Another avenue for further research would be in the opposite direction, namely, to incorporate more "realistic" assumptions. These efforts might start with relaxing certain simplifying assumptions used here. These might include: (1) allowing intrinsic appeal to vary by environmental position; (2) letting unused capacity generate some kind of additional competitive process; and (3) expanding dramatically the number of environmental positions and organizational actors.

Looking towards other issues not really considered here, we see interesting possibilities for extending the set of possible strategies for organizations in the model. In the model described above, organizations expand their engagement to new resource positions randomly if they grow in size, and distribute the growth in their engagement to this new resource position. This rule of niche expansion and engagement allocation, admittedly, is quite simple. Organizational managers, of course, typically intend to be strategic in entering and exiting resource positions, and follow more subtle rules for allocating engagement budgets. At least some of these could be simulated. Also, when investigating and comparing the efficiency of various strategies, one could allow for time-dependent strategies. For example, in some circumstances, it might be reasonable for organizations to focus their engagement for a while, and then expand. In other cases, early expansion might be more beneficial. Indeed, in the Hannan et al. (2007) story, the returns to engagement at new positions are delayed for some time.

Another extension to the model would be to connect the size of a resource position to the total amount of the engagement budget spent in the position. As the theory of density dependence (Hannan 1986) holds, a population's fundamental niche increases with the number of organizations in the population. As a parallel, it might make sense to argue that the legitimation and total demand in a position increase as organizations spend more resources and engage more at that position.

A different avenue for further research would be to incorporate entry and exit processes into the model. To keep the model tractable in this initial phase, we have not incorporated explicit entry and exit processes, but rather we kept the pool of organizations within each simulation run constant. Although resource partitioning can be studied by following a fixed set of organizations, much empirical work on the process builds on entry and exit processes. Thus, it would be interesting to see what additional assumptions about entry and exit would support the findings reported here.

Finally, one could compare the behavior of the model with relevant empirical data. Although finding data and comparing multiple populations with different levels of PoA and SA is a daunting task, one could try to work around these problems. For example, one could study populations that underwent external environmental shocks, and observe how the size distribution and organizational strategies change as a result of such shocks. As an example, consider a population that undergoes rapid technological progress: scale efficiencies often become stronger, affecting the size distribution of firms. If the change was externally generated (not a result of competition), one could test the size distribution before and after the change. Another possible test, following a similar line of argument, would be to compare the size distribution of organizational population that underwent legal-regulatory change such as the US banking sector. As always, we suspect that it is a mistake to underestimate the imagination and ingenuity of empirical researchers, and so we look forward to learning about even better research designs on these important issues.

Appendix: Description of the polarization measure

While there are a number of well-known measures of the concentration in the organizational size distributions (e.g., Gini, Herfindahl), there exists no established measure of the polarization of the size distribution. Here we use a polarization measure, Wolfson's p^* (Wolfson 1994), used in the income distribution literature. To our knowledge, this measure has not been used in the organizational literature, we briefly introduce it here.

After discussing why concentration measures and earlier measures of polarization are unable to grasp the 'disappearing middle,' Wolfson notes the duality between polarization and inequality. He introduces a polarization measure based on the Lorenz curve: by measuring the area between the Lorenz-curve and the tangent line of the Lorenz-curve. Formally, $p^* = (T - Gini/2)/mtan$, where $mtan =$ "*median tangent*", i.e., the slope of the tangent to the Lorenz curve at the 50th percentile; and T equals the area of the trapezoid defined by the 45-degree line and the median tangent.

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